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How Vulnerable are the Self-Employed? Evidence from Ugandan Small-Scale Entrepreneurs

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ABSTRACT *Due to small firm sizes and inter-linkages between household and business finances, small-scale entrepreneurs in developing countries are inherently vulnerable to temporary and permanent income shortfalls, and hence household poverty. While the International Labour Organisation (ILO) generally defines self-employment without employees as vulnerable employment, little empirical research has been done on the extent to which the self-employed are indeed vulnerable. This paper makes two main contributions: first, it operationalises the concept of vulnerability in the context of self-employment in developing countries by defining vulnerability as the risk of having business income below a living wage threshold. Secondly, it investigates the extent and correlates of vulnerability. Using a six-year balanced entrepreneur panel dataset from Kampala, Uganda, it is shown that the self-employed are heterogeneous with respect to vulnerability and observed earnings: 58–74% of the samples are classified as vulnerable in a given year and mostly earn incomes below the living wage threshold. Vulnerable entrepreneurs are shown to be significantly different from non-vulnerable entrepreneurs in several dimensions, including those that do not directly predict income.*

KEYWORDS: Entrepreneurship; Uganda; Africa; employment; vulnerability

1. Introduction

How vulnerable are the self-employed? According to the International Labour Organisation (ILO), own-account workers and contributing family workers are vulnerable by definition, while employers and employees are not. More than 70 per cent of employment in sub-Saharan Africa was thus classified as vulnerable employment in 2019 (ILO, 2020). While the simplification is useful and own-account workers may on average be more vulnerable than other groups, this blanket approach lacks clear empirical foundations (Ostermeier, Linde, Lay, & Prediger, 2015) and provides little information on the nature, extent, and severity of their vulnerability at

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the micro level. This paper contributes to filling that void by studying the vulnerability of Ugandan small-scale entrepreneurs.

Vulnerable employment is not decent employment in line with the ILO Decent Work Agenda, and the United Nation's 2030 Agenda.[1] The ILO motivates its definition of vulnerable employment as own-account work and contributing family work with reference to two key attributes of these categories, namely (i) a lower likelihood of having formal work arrangements (ILO, 2016), and (ii) inadequate earnings and low productivity (ILO, 2010). The use of vulnerable employment as a proxy for informal employment is backed by the observation that both measures are highly correlated and decline with economic development (ILO, 2016). While a consequent application of these definitions at the micro level would lead to some workers being classified as vulnerable but not informal, and vice versa, there is in practice admittedly little point in differentiating between vulnerable and non-vulnerable employment according to the ILO classification within the informal sector. Entrepreneurs can easily go from own-account worker to employer, as workers are hired or dismissed, without automatically becoming more or less vulnerable. It is precisely this conceptual blurriness around vulnerable and informal employment that makes the self-employed in the informal sector a highly relevant group to study when considering vulnerable employment.

This paper first operationalises vulnerability in the context of self-employment in developing countries. Drawing on the methods used in analysing vulnerability to poverty, vulnerability of the self-employed is defined as the risk of having a business income below a living wage. The rationale behind studying vulnerability to poverty is that when earnings fluctuate, identifying those at risk of falling into poverty may be more helpful from a policy perspective than somewhat arbitrary classifications of the poor and non-poor according to incomes observed at a specific point in time (Chaudhuri, Jalan, & Suryahadi, 2002; Dercon & Krishnan, 2000; Klasen & Waibel, 2013; Ligon & Schechter, 2003). In a study based on synthetic panels representing two-thirds of the population in sub-Saharan Africa, Dang and Dabalen (2019) show that while poverty rates declined over time in the majority of the countries they study, there was almost as much downward as upward mobility, thus underscoring the need to look beyond poverty rates.

Although vulnerability to poverty has traditionally been studied in agricultural contexts, the concept lends itself well to the study of self-employment. The fact that business incomes are highly stochastic, as are agricultural incomes, provides the rationale for focusing on vulnerability as the risk of inadequate earnings from self-employment. Income fluctuations are often modelled as a result of shocks that can be covariate (such as weather-related shocks or natural disasters, recent examples include Akampumuza & Matsuda, 2017; Salvucci & Santos, 2020; Skoufias, Vinha, & Beyene, 2021), or idiosyncratic (such as health shocks, see Atake, 2018; Ouadika, 2020). In the context of self-employment, covariate shocks could emanate from business cycles or sudden price fluctuations for inputs, while idiosyncratic shocks would be of a similar nature as in agricultural contexts. Fluctuations in income depend both on the likelihood of shocks occurring and the household's ability to cope with a shock (Hoddinott & Quisumbing, 2003b). Although micro-entrepreneurs bear entrepreneurial risks, their capability to absorb shocks is typically limited due to low household wealth, low saving rates, and small capital stocks. There is thus a high likelihood of shocks in one area spilling over into the other, which makes it all the more relevant to systematically study their vulnerability.

The empirical part of the paper investigates the extent, severity, and correlates of vulnerability by applying the concept of vulnerability to poverty in the context of small-scale entrepreneurship in Kampala, Uganda, using a six-year balanced panel dataset. Compared to much of the existing literature in the field, my analysis benefits from three methodological advances. Apart from using a conceptually and empirically well-justified living wage to define inadequate incomes, I also determine the probability threshold at which an entrepreneur is classified as vulnerable endogenously, thus avoiding the pitfalls of relying on arbitrary cut-off values. Instead of calculating probabilities using cross-sectional income variation, often a poor proxy for intertemporal variation, I am able to obtain more precise vulnerability estimates by drawing on individually-specific, intertemporal variance estimates.

My results show that roughly three-quarters of the entrepreneurs in the sample earned profits below the living wage in the past month, and between 50 and 70 per cent did so even in a good month. In the course of the six years under study, these shares increased slightly. Between 58 and 74 per cent of the sample were classified as vulnerable, with 6–13 per cent having this status while earning profits above the living wage in a given year. 15 to 21 per cent of the sample were classified as non-vulnerable while earning profits above the living wage. These findings highlight both the heterogeneity of the informal sector and the persistence of inadequate earnings for a substantial share of the self-employed. They provide evidence on the long-standing debate depicting self-employment in the informal sector either as low-productivity survivalism or as high-potential entrepreneurship.[2] My findings tie in well with existing evidence showing huge productivity differentials within informal sectors. Notably, Grimm, Knorringa, and Lay (2012) identify one to two-thirds of informal sector enterprises in six West African countries as survivalists with small capital stocks and low productivity, while the remainder is classified as either top performers with high capital stocks and high productivity, or constrained gazelles with low capital stocks and high productivity.

The results of this study also expose considerable downward, and limited upward mobility in the Kampala sample. While entrepreneurs earning profits above the living wage in a given year had a 47 per cent risk of dropping below the threshold in the following year, those earning profits below the living wage only stood a 15 per cent chance of improving their status in the following year. Entrepreneurs classified as vulnerable throughout the observation period earned profits below the living wage in most years. These results relate to earlier evidence on subsistence entrepreneurship in developing countries showing that the risks associated with entrepreneurial activities can lead to persistently low incomes by disincentivising investment (Dodlova, Göbel, Grimm, & Lay, 2015), or discourage entrepreneurial activity altogether due to risk aversion (Cieslik & D'Aoust, 2018). Another important aspect of vulnerability in self-employment that exceeds the scope of my study is the non-negligible risk of business failure, which is well-documented in developing country contexts (see Aga & Francis, 2017; Mead & Liedholm, 1998).

This paper is one of several recent contributions focusing on obtaining more precise and meaningful vulnerability estimates. One active field of research is the use of longer time horizons to capture poverty and vulnerability dynamics. Ward (2016) uses a balanced panel to examine poverty and vulnerability transitions in China and is thus methodologically closest to my approach. An alternative is the use of synthetic panels, which have been employed to study vulnerability in India (Dang & Lanjouw, 2015), Myanmar (Ferreira, Salvucci, & Tarp, 2021), and Tanzania (Aikaeli, Garcés-Urzainqui, & Mdadila, 2021). Other recent advances broaden the concept of vulnerability, focusing on fuzzy poverty measurement and multidimensional vulnerability (Pham, Mukhopadhaya, & Vu, 2021), as well as vulnerability to multidimensional poverty (Azeem, Mugera, & Schilizzi, 2018; Gallardo, 2020).

An active strand of literature that has gained further policy relevance due to the COVID pandemic focuses on drivers of and potential remedies to vulnerability to poverty. A dampening effect on vulnerability to poverty is found for social protection payments in Pakistan (albeit driven by a small number of programs; Azeem, Mugera, & Schilizzi, 2019), for financial inclusion in Ghana (Koomson, Villano, & Hadley, 2020), for membership in a microfinance group in India (Swain & Floro, 2012), and for participation in a support program for artisans in Kenya (Wang Sonne & Kinoti, 2022). Social assistance payments to other households, on the other hand, are found to exacerbate vulnerability to poverty in Ghana (Nkrumah, Annim, & Afful, 2021). In terms of individual strategies and choices, the adoption of innovative agricultural technologies in Ethiopia (Biru, Zeller, & Loos, 2020) and non-farm employment in Vietnam (Bui & Hoang, 2021) are found to decrease vulnerability. Most closely related to this paper, Sohns and Revilla Diez (2017) study to what extent taking up self-employment decreases vulnerability to poverty using panel data from Vietnam. They conclude that self-employment can significantly increase the probability of exiting poverty in economically developing regions, but can also exacerbate poverty risks in regions that are overly reliant on cash crop production.

The paper proceeds as follows: Section 2 provides the backdrop with an overview of poverty, vulnerability, and self-employment in Uganda. Section 3 combines the concepts of vulnerable employment and of vulnerability to poverty to arrive at a concept of vulnerability in self-employment as the risk of having business income below a living wage threshold. This new concept is then applied to the context of self-employment in Kampala by analysing both the inadequacy of earnings and vulnerability to inadequate earnings over a six-year time horizon in a balanced panel dataset. Section 5 concludes.

2. Poverty, vulnerability, and self-employment in Uganda

After a period of impressive poverty reduction that saw the share of Uganda's population living on <1.90 USD/day drop from 66 per cent in 2002 to 36 per cent in 2012, the poverty headcount hovered at around 41 per cent until 2019 (see Figure 1). This setback can be attributed to an overall economic slowdown and droughts in 2016/17 (Mejia-Mantilla, 2020). The share of the population living on <3.20 USD/day declined more slowly and still stood at 70 per cent in 2019, while 89 per cent of the population lived on <5.50 USD. An analysis by Atamanov, Mukiza, and Ssennono (2022) based on the 2019/20 Uganda National Household Survey and the national poverty line finds poverty and vulnerability rates to be highest in rural areas, where vulnerability is also much higher than poverty. Vulnerability in urban areas is found to be mostly risk-induced, driven by idiosyncratic shocks leading to fluctuations in consumption, whereas vulnerability in rural areas tends to be in equal parts risk-induced and poverty-induced. At the individual level, the strongest predictor of vulnerability status was the education of the household head, with higher education levels being associated with lower vulnerability. The authors find no strong association between vulnerability and the household head's employment status (employed/not employed/subsistence agriculture) but identify significant differences with respect to the household head's sector of employment. While Atamanov et al. (2022) do not consider the gender of the household head explicitly, Akampumuza and Matsuda (2017) find

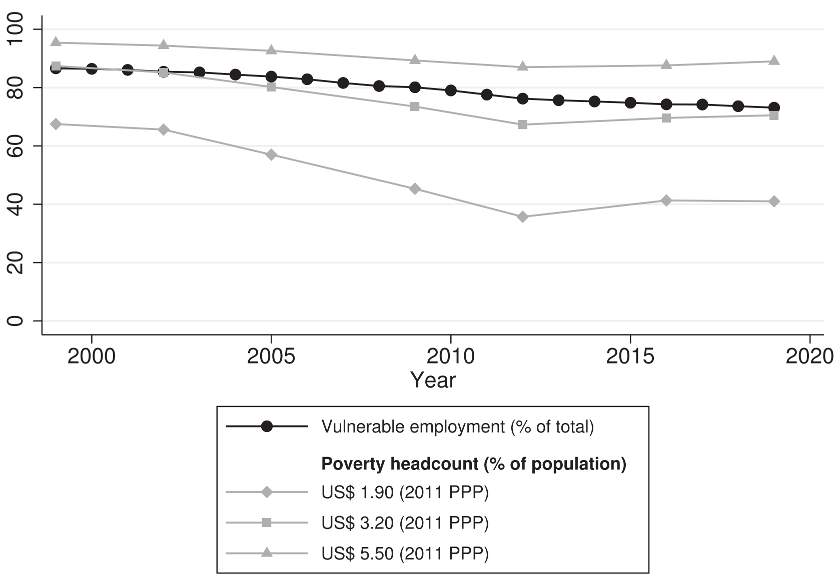

Figure 1. Vulnerable employment and poverty in Uganda 1999–2019.

that female-headed households are disproportionately vulnerable in a study of urban households in Uganda's Kumi district. Vulnerable employment in Uganda declined in the past 20 years but was still high at 73 per cent in 2019 (ILO, 2020). There is a marked gender gap, with 80 per cent of female employment versus 67 per cent of male employment being vulnerable, which is illustrative of a global tendency for women being more often in vulnerable employment (Lo Bue, Le, Santos Silva, & Sen, 2022).

3. Operationalising vulnerability in self-employment

3.1. Concepts

This paper draws on two different notions of vulnerability: the concept of vulnerable employment as defined by the ILO, and the concept of vulnerability to poverty. Vulnerable employment is defined in terms of status in employment as 'the sum of own-account workers and contributing family workers'. The characterisation of this work as vulnerable is motivated by the assertion that '[v]ulnerable employment is often characterized by inadequate earnings, low productivity and difficult conditions of work that undermine workers' fundamental rights'. I draw on the understanding of vulnerability as expected poverty (Ceriani, 2018; Chaudhuri et al., 2002; Hoddinott & Quisumbing, 2003a; Mosley, Holzmann, & Jorgensen, 1999), defining vulnerability as 'the likelihood that at a given time in the future, an individual will have a level of welfare below some norm or benchmark' (Hoddinott & Quisumbing, 2003b). This paper focuses on the dimension of inadequate earnings and low productivity, thus using income to approximate welfare. The vulnerability definition given by Hoddinott and Quisumbing can be expressed as

$$V_{it} = Pr(y_{i,t+1} \leq z), \tag{1}$$

where vulnerability V of individual i in period t is the probability that income y_i in period $t+1$ falls below a certain threshold z. In order to obtain vulnerability estimates, meaningful definitions are needed for the elements y_{it}, z, and a probability threshold that places individuals in the 'vulnerable' category. z corresponds to the norm or benchmark specified by Hoddinott and Quisumbing on the one hand, and the idea of (in-)adequate earnings on the other hand. Rather than using poverty rates as many studies do, I define the benchmark in terms of a *living wage*. Understood as 'a wage adequate to maintain a reasonable standard of life as this is understood in their time and country',[3] the provision of a living wage was one of the ILO's founding principles in 1919 (Reynaud, 2017). The concept of a living wage has now become synonymous with a decent wage (Anker & Anker, 2017). Methodologies used to estimate living wages in developing countries are typically similar to the World Bank's national poverty lines in relying on household survey data and differentiating between only two expense groups, namely food and other costs. These approaches are criticised by Anker (2011) because they often yield low living wage estimates reflecting the current (less than decent) living conditions, and because they treat non-food costs as a black box. Addressing these shortcomings, Anker and Anker (2017) develop a novel methodology assessing the cost of living based on more fine-grained expense categories as well as a small margin for unforeseen expenses. Living wage estimates based on the Anker and Anker methodology and cost of living surveys are published by the Wage Indicator Foundation.

Income y is defined as an entrepreneurs' business profits. Future profits Π_{it+1} are further assumed to be a function of X_{it}, a vector of observable and time-varying factors including capital and labour, owner and firm characteristics, individual-specific and time-invariant factors α_i, time effects δ_{t+1}, and time-varying idiosyncratic factors ε_{it+1}:[4]

$$\Pi_{it+1} = \Pi(X'_{it}, \alpha_i, \delta_{t+1}, \varepsilon_{it+1}). \tag{2}$$

In logarithms, this can be expressed as

$$ln\Pi_{it+1} = X'_{it}\beta + \alpha_i + \delta_{t+1} + \varepsilon_{it+1}. \tag{3}$$

Following Ward (2016), vulnerability, as defined in Equation (1) and conditional on covariates, can then be expressed as

$$V_{it} = Pr\left[\Pi_{i,t+1} = \Pi(E\left[X'_{i,t}\right], \alpha_i, \delta_{t+1}, E[\varepsilon_{i,t+1}]) \leq z|X'_{it}, \alpha_i, \varepsilon_{it}\right]. \tag{4}$$

In order to obtain this probability, estimates of the variance and expected values of Π_{it+1} are needed. The conditional variance of future profits is defined as the average squared deviation of observed profits in $t + 1$ from their expected value:

$$Var\left[ln\Pi_{it+1}|X'_{it}, \hat{\beta}, \hat{\alpha}_i, \hat{\delta}_{t+1}\right] \quad = \hat{\sigma}^2_{\Pi_i} \quad = T_i^{-1}\sum_{t=1}^{T_i}(ln\Pi_{it+1} - E\left[ln\Pi_{it+1}|X'_{it}, \hat{\alpha}_i, \hat{\delta}_{t+1}\right])^2. \tag{5}$$

I further assume that every entrepreneur has their own profit distribution in which profits are log-normally distributed through time. This assumption avoids the pitfalls of using cross-sectional variance to proxy for inter-temporal variance, as is common in vulnerability studies based on cross-sectional data (Hoddinott & Quisumbing, 2003b). Given the expected value and variance for Π_{i+1}, vulnerability as the probability of having profits below the living wage can then be obtained using the normal cumulative distribution function Φ :

$$V_{it} = \Phi\left(\frac{lnz - E\left[ln\Pi_{it+1}|X'_{it}, \hat{\alpha}_i, \widehat{\delta_{t+1}}\right]}{\sqrt{Var\left[ln\Pi_{it+1}|X'_{it}, \hat{\alpha}_i, \widehat{\delta_{t+1}}\right]}}\right). \tag{6}$$

Approaches differ when it comes to defining a probability threshold that classifies individuals as vulnerable or non-vulnerable. Most applied papers use a threshold of 50 per cent (e.g. Atamanov et al., 2022; Christiaensen & Subbarao, 2005; Ouadika, 2020), the observed poverty rate, or another fixed value (Ward, 2016, for example, uses a threshold of 0.33). The 50 per cent probability threshold is the most widely used and has an intuitive appeal, corresponding to an equal probability of being poor or non-poor and with an expected income of exactly the poverty line (Pritchett, Suryahadi, & Sumarto, 2000). I determine the probability threshold endogenously, following the argument of Hohberg, Landau, Kneib, Klasen, and Zucchini (2018) that doing so can considerably improve the predictive performance of vulnerability estimates.

3.2. Data

The analysis in this paper is based on a balanced, annual panel dataset collected by the author's institutions as part of a research project on the dynamics of MSEs over the 2012–2018 period[5] in Kampala, Uganda. Sampling followed a two-stage stratified random sampling procedure. After identifying 220 business zones in Kampala, 16 zones were randomly selected as primary sampling units. A door-to-door listing survey of all enterprises in these zones was conducted in 2012 and repeated in 2015. Out of the total enterprise population of these zones, a sample of 450 enterprises was then drawn randomly after stratification by industry sector. To obtain somewhat homogeneous sub-samples and a gender balance, certain industry sectors were over-sampled. The same entrepreneurs are interviewed each year, with drop-outs (10–15% per year) being replaced by similar entrepreneurs from the same stratum. The dataset is very broad in thematic coverage, with topics ranging from general enterprise information (such as value and structure of physical business assets, labour and physical inputs, outputs, sales and expenditures, profits), business practices, and financial management, to characteristics and attitudes of the entrepreneur (age, gender, education, cognitive ability, financial knowledge, time and risk preferences, personality traits), as well as socio-demographic characteristics of the entrepreneur and the household s/he resides in (household composition and wealth).

After dropping observations with missing values for key variables and individuals who were not observed throughout the whole study period, a balanced panel of 226 entrepreneurs observed throughout 2013–2018 remains. Table 1 illustrates the industry sector distribution as well as key enterprise, owner, and household characteristics observed in 2013. Just over half of the sample consists of manufacturing businesses, with printing and paper products as well as textile and wearing apparel being important categories, just over a quarter are retail businesses, and one services sector (hair dressing and beauty) makes up about 14 per cent of the sample. The most striking observation is that monthly profits are low at very high labour inputs, with the median entrepreneur earning 181 USD (all monetary values in 2012 prices), and entrepreneurs' average working hours at a staggering 302 h per month. Regarding socio-economic characteristics, 44 per cent of the sample only have primary school education, over a quarter have completed their O-levels, and another quarter have completed their A-levels or obtained a university degree. A little over 40 per cent of the sample are female. An overwhelming majority of entrepreneurs are either the household head or his spouse, also mirrored in 57 per cent

Table 1. Descriptive statistics, 2013 sample

Variable	Obs.	Mean/%	Std. Dev.	Med.
Industry sector				
Hair and beauty	226	13.72	34.48	0
Manufacturing (printing/paper)	226	12.39	33.02	0
Manufacturing (textile)	226	14.60	35.39	0
Manufacturing (remaining)	226	28.76	45.37	0
Other	226	3.10	17.36	0
Retail/wholesale (remaining)	226	15.04	35.83	0
Retail (clothing, footwear, leather)	226	7.08	25.71	0
Retail (electric)	226	5.31	22.47	0
Firm characteristics				
Profit (2012 USD)	226	315.80	494.15	181
Capital stock (2012 USD)	226	2137.01	7458.52	318
Total labour (h/month)	226	670.42	587.95	504
Owner labour (h/month)	226	308.01	82.93	302
Own-account worker (%)	226	42.04	49.47	0
Firm age (years)	226	8.41	7.02	6
Registered (URA,%)	226	6.19	24.16	0
Personal characteristics				
Education—Primary (%)	226	43.81	49.72	0
Education—O-level (%)	226	27.88	44.94	0
Education—A-level (%)	226	16.81	37.48	0
Education—University (%)	226	8.41	27.81	0
Age (years)	226	35.73	9.78	34
Female entrepreneur (%)	226	41.15	49.32	0
Married (%)	226	56.64	49.67	100
Household size	226	4.84	2.37	5
Respondent HH head/spouse (%)	226	97.35	16.11	100
Access to bank account (%)	226	71.68	45.15	100
Credit constrained (%)	225	48.89	50.10	0
Total savings (2012 USD)	215	731.04	2280.97	254

of entrepreneurs being married, a relatively high average age of 35 years, and a mean household size of five persons. While 72 per cent have access to a bank account, 49 per cent report being credit constrained.

4. Inadequate earnings and vulnerability

4.1. Inadequate earnings over time

Our sample consists of relatively small urban households, with an average of 1.8 working adults and 2 children aged 15 or younger. The minimum living income is hence defined as the income required for one earner (the entrepreneur) in a family with 1.8 working adults and 2 children. The monthly living wage calculated for Uganda in 2018 is 302 USD (2012 prices) for a standard family as defined above (Guzi & Kahanec, 2018).[6]

The left panel of Figure 2 shows the percentage of the self-employed with incomes below the family living wage for each year from 2013 to 2018. For all years, profits had been below the living wage for at least 70 per cent of the sample in the past month, for more than 80 per cent in some months, and over 50 per cent of the sample always had profits below the living wage. An upward trend is observable, with the share always earning profits below the living wage reaching 61 per cent in 2018. The right panel of Figure 2 illustrates all transitions in the sample and shows that although the percentages in the left panel do not fluctuate a lot, there is some, albeit mostly downward, mobility: of those above the living wage threshold in one period, 47 per cent dropped below the living wage in the following period. Of those with profits below the living wage, 15 per cent managed to increase their profits to more than the living wage in the following period, while 85 per cent did not.

The main reason behind assuming the average household composition, as opposed to adjusting the living wage to individual household compositions, is that we are concerned more with the earnings potential of self-employment in terms of providing for an average family than with individual family compositions, which may be endogenous to household income. One might worry about the standard family assumption biasing the results, for example, if households with lower incomes had systematically more dependents. To check whether this is the case, I present a modified classification based on the past month's profits and a living wage threshold adjusted for household composition. This is done by calculating the necessary expenditures in different categories for a given number of (working) adults and dependent children following

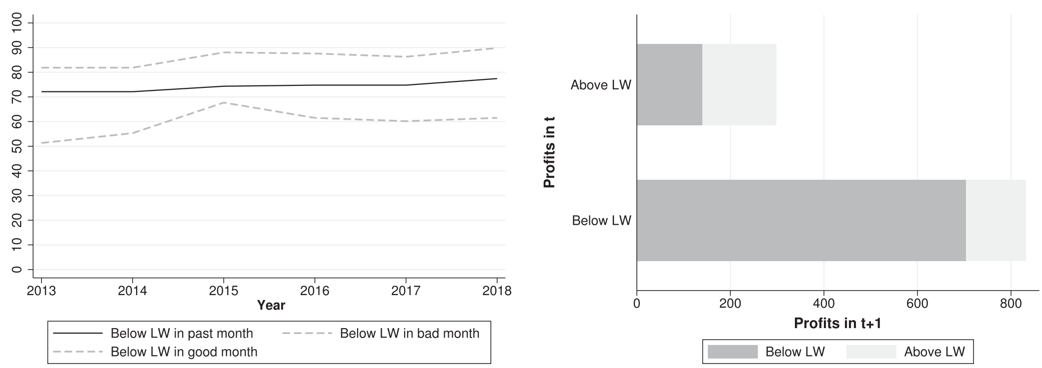

Figure 2. Inadequate earnings over time. (a) Percentage of entrepreneurs with profits below family living wage by year. Balanced panel ($N = 226$). (b) Movements between periods around the living wage threshold. Balanced panel, pooled 2013–2018.
Source: Author's calculations based on MSE panel.

the methodology outlined in Guzi and Kahanec (2018) and the expenditures for December 2018. As illustrated in Figure A1, both ways of specifying the living wage lead to the same conclusions for at least 90 per cent of the sample, with around 70 per cent being classified as having profits below the living wage in both cases, and roughly 20 per cent being above in both cases. Given these very minor differences in results, I uphold the assumption of the standard family and continue using the uniform living wage threshold.

4.2. *Determinants of income*

Table 2 displays the results of estimating Equation (3) using random effects (RE). The dependent variable is logarithmic profits in the following year, and the main independent variables are firm and owner characteristics. Results are largely as expected, with the size of the capital and labour inputs having a significantly positive effect on profits. Firms in central Kampala realise significantly higher profits, while profits in the hair dressing and beauty industry are significantly lower than in manufacturing. Household wealth and savings have significantly positive effects on profits, which can be explained in terms of wealth and savings mitigating credit and liquidity constraints. Characteristics of the business owner matter for profits as well. Women realise around 40 per cent lower profits than men even after controlling for firm size and sector. While age and education do not have a significant impact on profits, respondents who score higher on a cognitive ability test do better in business.

There is an ongoing discussion about including or excluding shocks in this type of exercise, as the ultimate objective is to predict income. One might argue that idiosyncratic shocks are contained in the error term and their expected value is zero. To test whether this assumption holds, I include several shocks that occurred between t and $t+1$ in column 2 and test for their joint significance. The non-business shocks included are *health shocks*, defined as having been ill in the past four weeks, having recently been *divorced, widowed, or having lost a wage earner*, and *household asset shocks*, defined as a decrease in the household asset index of more than one standard deviation. Business shocks included are *business temporarily closed*, coded as one if the business was not in operation throughout the full 12 months, and *business asset shock*, defined as a decrease in business assets of more than one standard deviation. While only one coefficient is individually significant, all coefficients share a negative sign and are jointly significant.

While the focus here is on predicting profits rather than on estimating and interpreting individual coefficients, I conduct several robustness checks addressing threats to the validity of the results (see Section E in the Online Appendix for estimation tables). First, I re-estimate the equation using Fixed Effects (FE), which allows for the presence of unobserved individual-specific and time-invariant factors influencing future profits. However, the model has very low predictive power given low within-variation in key explanatory variables like labour hours or capital stocks, with coefficient estimates that are implausibly close to zero and largely insignificant. I, therefore, focus on the RE results, which draw predictive power from a combination of within and between variation. Secondly, the results in Table 2 may be influenced by the treatment of negative or zero profits, which were set to one before applying the logarithmic transformation. Such cases may be highly informative for the purposes of this analysis, as they likely represent strong downward fluctuations. I conduct a robustness check using an Inverse Hyperbolic Sine (IHS) transformation of the dependent variable, which preserves certain desirable properties of the log transformation, such as attenuation of extreme values and easy coefficient interpretation in terms of elasticities, while also being able to accommodate negative values. The estimation results remain very similar and consistent, with minor changes in the size and significance of the coefficients of individual shocks. Another concern may be omitted variable bias, for example, due to the exclusion of important factors, such as past values of profits from the analysis. Past profits could influence future profits through alternative modes of saving and/or investment that are not fully captured in the data, for example, investments in

Table 2. Predicting profits in $t+1$

	(1)	(2)
	RE	RE
Capital stock (2012 USD)	0.066**	0.066**
	(0.023)	(0.023)
Log labour hours	0.120*	0.120*
	(0.053)	(0.053)
Firm age	0.026	0.025
	(0.018)	(0.018)
Firm age squared	−0.001	−0.001
	(0.001)	(0.001)
Registered with URA	−0.101	−0.081
	(0.091)	(0.090)
Credit constrained	−0.072	−0.069
	(0.068)	(0.067)
Industry sector: hair and beauty	−0.430***	−0.446***
	(0.113)	(0.111)
Industry sector: retail	−0.072	−0.068
	(0.105)	(0.103)
Industry sector: other	−0.183	−0.184
	(0.133)	(0.131)
Central Kampala	0.382***	0.373***
	(0.087)	(0.086)
Household wealth index	1.468***	1.624***
	(0.292)	(0.293)
Log total savings	0.107***	0.104***
	(0.023)	(0.023)
Age in years	0.001	−0.002
	(0.029)	(0.029)
Age squared	−0.000	−0.000
	(0.000)	(0.000)
Female	−0.422***	−0.392***
	(0.089)	(0.086)
Edu: completed O-level	0.003	−0.014
	(0.088)	(0.086)
Edu: completed A-level	0.096	0.071
	(0.111)	(0.111)
Edu: completed university	0.013	−0.005
	(0.139)	(0.138)
Cognitive ability	0.074*	0.077*
	(0.034)	(0.034)
Health shock ($t+1$)		−0.000
		(0.073)
Divorced, widowed, HH lost wage earner ($t+1$)		−0.101
		(0.062)
Household asset shock ($t+1$)		−0.206
		(0.110)
Business temporarily closed ($t+1$)		−0.252*
		(0.127)
Business capital shock ($t+1$)		−0.197
		(0.121)
Test for joint significance of shocks		
$\chi^2(5)$		15.4
Prob > χ^2		.0089
R-squared (overall)	0.403	0.414
R-squared (within)	0.029	0.034
R-squared (between)	0.645	0.664

(*continued*)

Table 2. (*Continued*)

	(1)	(2)
N	1061	1060
N (clusters)	226	226

Notes: Standard errors clustered at individual level in parentheses. *, **, *** denote significance at 0.05, 0.01, and 0.001 levels of significance, respectively. The dependent variable in Columns (1) and (2) is logarithmic profits, where non-positive values are set to one before the logarithmic transformation. Base categories: Industry sector—manufacturing. Education—primary education or less. Gender: male. Year dummies included. Outliers are identified according to Welsch and Kuh's (1977) DFITS measure and excluded from estimation if DFITS exceeds $\pm 2 * \sqrt{\frac{p}{N}}$.

non-physical capital. I test the robustness of these results by including profits in $t-1$ in the estimation. Again, while the coefficient of past profits is positive and significant, the results for all other coefficients remain robust. Finally, I conduct a Chow test for parameter stability over time by re-estimating the model and interacting all coefficients with year dummies. The coefficients of all interaction terms are not significantly different from zero for any year, suggesting that pooling data over survey years is unproblematic.

4.3. *Computing vulnerability*

After obtaining predicted profits using the RE regression results in Column 1 of Table 2, conditional, inter-temporal variances for each individual can be calculated as defined in Equation (5). While more than 60 per cent of these individual-level variances are lower than the conditional variance calculated from the cross-section, some of the remaining values are considerably higher. Notably, high conditional variances can be observed at all levels of the profit distribution, including for zero or negative profits (Details in Online Appendix Figure C1). These observations illustrate that while many entrepreneurs may not see very strong deviations in profits from their (often low) expected values, there is a sizeable minority experiencing strong fluctuations in profits.

Using these conditional variances, vulnerability as the probability of having profits below the living wage can be calculated for each individual as specified in Equation (1).[7] The share of entrepreneurs who will be classified as vulnerable or non-vulnerable now depends on the probability cut-off, which I determine endogenously to optimise predictive performance. Figure 3 depicts a receiver operating characteristic (ROC) curve for all probability cut-off points from 1 to 99 per cent plotting the true positive rate (TPR), that is, the ratio of entrepreneurs whose earnings are correctly predicted to be below the living wage, against the false positive rate (FPR), that is, the ratio of entrepreneurs whose earnings are incorrectly predicted to be below the living wage. The higher our probability threshold, the more entrepreneurs will be identified as vulnerable, and the higher both the TPR and FPR. The conventionally chosen 50 per cent probability threshold would imply a high TPR of 92 per cent, but also an undesirably high FPR of 63 per cent. The ideal probability threshold should be situated as far as possible in the top-left corner of the graph (Hohberg et al., 2018), thus simultaneously maximising the TPR and minimising the FPR. I determine the threshold value endogenously as the maximum value of the targeting differential given a TPR of at least 80 per cent. The targeting differential is defined as TPR-FPR and was proposed by Ravallion (1999, 2009) as a measure of how well the poor are identified, where higher values indicate better targeting. The endogenously chosen threshold is 59 per cent, which combines a TPR of 81 per cent with an FPR of 41 per cent (Table 3).

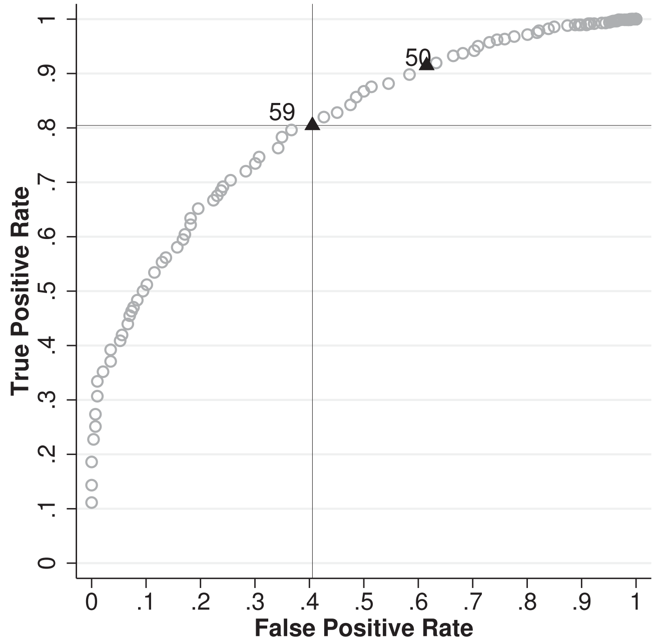

Figure 3. Receiver operating characteristic (ROC) curve for probability thresholds from 1 to 99. The ROC curve plots the true positive rate (TPR) against the false positive rate (FPR), that is, the share of observations that are correctly (TPR) or incorrectly(FPR) identified as having profits below the living wage in $t+1$.

4.4. How vulnerable are the self-employed?

Figure 4(a) illustrates the resulting vulnerability classifications as described in Section 3 for the 2013–2017 period. Between 51 and 65 per cent of the sample are classified as vulnerable in a given year while having profits below the living wage, thus suggesting that their earnings are chronically low. 15 to 21 per cent of the sample are classified as non-vulnerable while having profits above the living wage threshold, indicating a somewhat stable situation. Another 10–21 per cent of the sample are not classified as vulnerable, but earn less than the living wage threshold, while 7–13 per cent of the sample had profits above the living wage and were classified as vulnerable. Overall, the share of the sample classified as vulnerable remains high at between 73 and 74 per cent from 2014 onwards, which is in line with the stagnating poverty rates in Uganda described in Section 2.

As Figure 4(b) shows, about two-thirds of the sample were classified as vulnerable most of the time (53% in 5/5 periods, 13% in 4/5 periods). Those always identified as vulnerable throughout the observation period spent an average of 4.6/5 periods with profits below the living wage, suggesting that their earnings were indeed chronically inadequate. Seventeen per cent of the sample were never classified as vulnerable but still had profits below the living wage in roughly 2 periods.[8] Small shares of between 5 and 6 per cent, respectively, were classified as vulnerable for one to three periods, and had profits below the living wage for an average of 2.5–3.4 periods. Overall, Figure 4(b) illustrates not just the high prevalence of inadequate earnings in the sample, but also the fact that income fluctuations lead to frequent status changes and few entrepreneurs permanently earn more than the living wage.

One might be concerned about vulnerability being understated due to survivorship bias in the balanced panel, meaning that drop-outs, some of which were likely business failures, may have been systematically more vulnerable than those remaining in the sample. Addressing this concern, I compute vulnerability separately for two sub-samples using the 2013 cross-section, namely ‘stayers’ who remained in the sample until 2018, and ‘drop-outs’ who left the sample

Table 3. Who are the vulnerable?

Variable	Vuln.	Non-vuln.	Diff.	p
Hair and beauty (%)	21.37	3.16	−18.22	0.000
Manufacturing (printing/paper, %)	3.82	24.21	20.39	0.000
Manufacturing (textile, %)	22.90	3.16	−19.74	0.000
Manufacturing (rem., %)	17.56	44.21	26.65	0.000
Other sector (%)	1.53	5.26	3.74	0.144
Retail/wholesale (rem., %)	18.32	10.53	−7.79	0.094
Retail (clothing, footwear, leather, %)	9.92	3.16	−6.77	0.035
Retail (electric, %)	4.58	6.32	1.74	0.577
Profit (2012 USD)	161.04	529.22	368.19	0.000
Capital stock (2012 USD)	506.09	4385.96	3879.87	0.001
Total labour (h/month)	435.97	993.72	557.75	0.000
Owner labour (h/month)	305.93	310.89	4.96	0.645
Own-account worker (%)	58.78	18.95	−39.83	0.000
Firm age (years)	7.09	10.23	3.14	0.002
Registered (URA, %)	1.53	12.63	11.10	0.003
Credit constrained (%)	33.59	24.21	−9.38	0.123
Central Kampala (%)	15.27	68.42	53.15	0.000
Total savings (2012 USD)	195.40	1474.99	1279.58	0.001
Female entrepreneur (%)	58.78	16.84	−41.94	0.000
Education—None (%)	3.05	1.05	−2.00	0.278
Education—Primary (%)	55.73	27.37	−28.36	0.000
Education—O-level (%)	28.24	27.37	−0.88	0.885
Education—A-level (%)	10.69	25.26	14.58	0.006
Education—University (%)	2.29	16.84	14.55	0.001
Cognitive skills	−0.19	0.19	0.38	0.004
Age (years)	34.71	37.15	2.44	0.065
Household wealth index	0.46	0.66	0.20	0.000
Female-headed household (%)	16.03	6.32	−9.71	0.018
N of children	1.94	1.92	−0.02	0.917
N of wage earners in household	1.79	1.86	0.08	0.537
Married (%)	54.20	60.00	5.80	0.386

Two-sample t-tests vulnerable versus non-vulnerable, 2013 sample, $N = 226$.

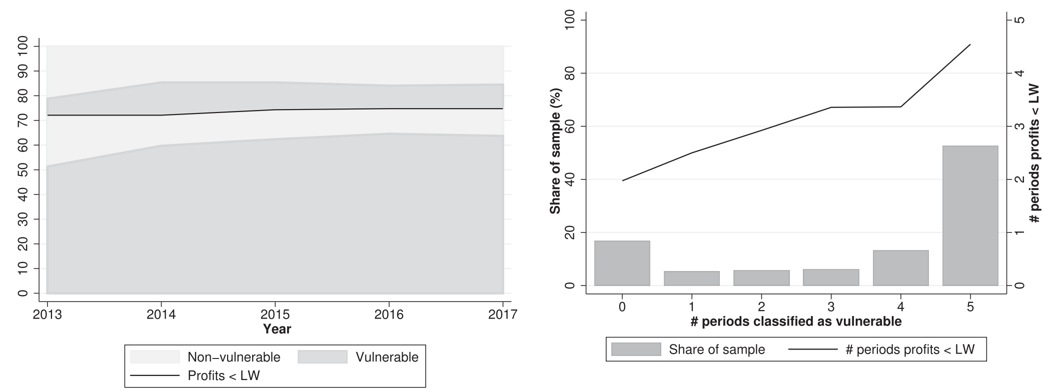

Figure 4. Vulnerability over time. (a) Percentage of entrepreneurs by vulnerability classification. (b) Number of periods classified as vulnerable and average number of periods spent with profits below the living wage.
Source: Author's calculations based on MSE panel.

after 2014 (see Online Appendix F for details). I find no difference in the share classified as vulnerable in the two sub-samples, suggesting that the vulnerability results in this section are not biased downward due to drop-outs being excluded. This result also reflects the absence of significant differences between the groups in the share of entrepreneurs with observed profits below the living wage in 2014 and other important factors, such as firm size, individual characteristics, or household composition.

4.5. *Who are the vulnerable?*

Identifying characteristics associated with being vulnerable is one of the key objectives of this paper. It is not a straightforward exercise, however, as a regression-based analysis would simply reproduce the results of the underlying profit estimation (cf. Hoddinott & Quisumbing, 2003b; Ward, 2016). I conduct two-sample *t*-tests comparing the means of different characteristics between those classified as vulnerable and non-vulnerable. Importantly, this is a purely descriptive exercise and should be interpreted in terms of identifying *correlates* rather than determinants of vulnerability. As Table 3 shows, there are significant differences in virtually every dimension. Entrepreneurs classified as vulnerable are much more likely to be in the (low-productivity) sectors of hair dressing and beauty or tailoring, and still somewhat more likely to be in the retail of clothes and footwear, but significantly less likely to be in printing or other manufacturing sectors. The vulnerable also have considerably lower factor inputs, with the average capital stock size being about 12 per cent of the non-vulnerable, and average monthly labour hours being less than half the size at a significantly higher likelihood of being an own-account worker. These numbers implying very different capital–labour ratios are in line with the concentration of the vulnerable in less capital-intensive sectors, but above and beyond that, their very low capital stocks are also in line with significantly lower household wealth and savings. Unsurprisingly, vulnerable entrepreneurs also have significantly younger firms that are less likely to be formally registered, and less likely to be in central Kampala. They are significantly more likely to be female and have only primary school education or less, and have lower average cognitive ability.[9] While there is no significant age difference, vulnerable entrepreneurs are significantly more likely to live in female-headed households. Interestingly, there is no significant difference in marital status, the average number of children in the household, or the number of working members in the household. It is worth noting that vulnerability classifications do not explicitly take this combination of socio-demographic characteristics into account: marital status, gender of the household head, and the number of working household members do not significantly predict profits and were not included in the estimation, nor did they have any relevance for the living wage threshold. The fact that these characteristics differ significantly between groups, however, suggest that household characteristics reflecting coping capability are indeed correlated with vulnerability status.

5. Conclusion

This paper critically reviews the ILO definition of vulnerable employment as own-account work and contributing family work. Based on the observation that there is considerable overlap between vulnerable employment and informal employment, and that a distinction between vulnerable and non-vulnerable work along status-in-employment categories would not be meaningful in the informal sector, I conduct an empirical investigation of the vulnerability of the self-employed. The analysis is based on a balanced panel dataset of largely informal small-scale entrepreneurs in Kampala, Uganda, covering the 2013–2018 period. The first key result underscores the heterogeneity of the self-employed: while the majority of the sample is classified as vulnerable and sometimes or always have incomes below the living wage, around 15 per cent of the sample are not vulnerable and mostly earn incomes above the living wage. Secondly, these vulnerability classifications defy easy categorisation in terms of status in employment or formalisation: 41 per cent of the vulnerable are employers, and 19 per cent of the non-vulnerable are own-account workers. Similarly, 87 per cent of the non-vulnerable run informal businesses, which suggests informality is not necessarily a strong predictor of vulnerability. Sector and capital stocks, as well as gender, education, cognitive skills, savings, and household wealth, all emerged as important correlates of vulnerability.

To sum up, while many of the self-employed in general and own-account workers, in particular, may be vulnerable to inadequate earnings, neither a blanket classification of all own-account workers as vulnerable nor a blanket classification of all employment in the informal sector would do justice to the complexity of the phenomenon. The policy implications of my findings are twofold: first, although defining vulnerable employment in terms of status-in-employment may be a useful simplification to produce macro statistics, it is not a sufficient criterion to identify vulnerable groups at the micro level. Policy interventions aiming to address vulnerability in employment thus need a set of context-dependent criteria to identify and reach target populations, and should focus efforts on improving employment conditions rather than employment status. Secondly, and relatedly, these findings speak to the larger debate on how small-scale entrepreneurship, particularly own-account work, should be evaluated from a policy perspective. When understood as vulnerable employment taken up due to a lack of options, own-account work should be phased out and replaced by more stable alternatives, such as dependent employment. When seen as potentially productive entrepreneurship, however, it should be encouraged. In line with earlier contributions, my results suggest that while the majority of the sample is arguably vulnerable, the more positive interpretation does apply for a non-negligible share. Notably, vulnerability is defined here in terms of a living wage, which stands for a *decent income* and is considerably higher than national or international poverty lines. Compared to large parts of the rural population, many urban entrepreneurs are still relatively well off. An improved understanding of vulnerable employment in low-income countries thus needs to acknowledge that although self-employment may often fail to provide the economic stability and good working conditions that would be desirable for all, it can also be a comparatively successful medium-term strategy in African labour markets.

Notes

1. Note that the share of vulnerable employment was an indicator for the Millennium Development Goals (MDGs) but is not an SDG indicator. The share of informal employment is an indicator for Sustainable Development Goal 8.
2. The survivalism viewpoint is associated with the ILO and described in Tokman (2007), whereas the high-potential view is associated with the work of Hernando de Soto. See de Mel, McKenzie, and Woodruff (2010) for an empirical contribution to the debate.
3. Article 427, ILO Constitution.
4. The modelled relationship between *future* profits and *current* levels of the factors of production and characteristics stays true to the understanding of vulnerability as the risk of having an inadequate income in the future, as implemented similarly by Christiaensen and Subbarao (2005). This approach avoids the assumption that current income proxies for future or permanent income, which is often made in studies relying on cross-sectional data and modelling income and its determinants contemporaneously.
5. While the listing survey and the first annual survey took place in 2012, the analysis in this paper uses data from 2013 onwards, as not all variables were available for 2012.
6. This figure is based on the December 2018 WageIndicator Cost of Living survey. It represents the median cost required to meet a family's basic needs such as food, housing, transport, health, education, and tax deductions. For a single person, the living wage was 191 USD.
7. Notably, this estimation relies on the assumption that predicted profits are log-normally distributed through time. Shapiro-Wilk tests of log-normality reported in Online Appendix Table D1 reject the hypothesis that predicted profits are log-normally distributed only for six entrepreneurs (3% of the sample). I thus accept log-normality as a reasonable working assumption.

8. The fact that those never classified as vulnerable still had observed profits below the living wage in some periods might seem surprising, but is a result of a relatively high probability cut-off: those classified as non-vulnerable still had an average probability of 43 per cent of having profits below the living wage.
9. The cognitive skills measure is based on performance solving Raven matrices.

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Ethical approval

This research project was approved by the Uganda National Council for Science and Technology (UNCST) under the reference *SS2892* in September 2012. The approval was renewed under the same reference in March 2016 and August 2018. All study participants were informed about their rights and gave written consent before each yearly interview.

Disclosure statement

No potential conflict of interest was reported by the author.

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Data availability statement

The dataset used in this study is documented at https://www.giga-hamburg.de/en/publications/research-datasets/mse-survey-kampala-2012-2018. Replication files are available under https://doi.org/10.7802/2572.

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